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Fine-scale spatial distribution of biomass using satellite images

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Spatial information on the distribution of biomass is an important issue for monitoring and managing the environment. It is a prerequisite for successful forest fire management and for predicting fire intensity and fire behaviour, but estimates of biomass are time consuming and expensive and need to be done depending on size classes. We propose a method that takes into account the contemporary use of an allometric approach and remote sensed data from Very High Resolution (VHR) satellite images to obtain distribution maps of biomass subdivided into different components while keeping plant-destructive collection of data to a minimum. To test the feasibility of distributing biomass into classes, we subdivided biomass into two size classes according to the size of leaves (thickness) and branches (diameter). This is an approach that can be adapted to both fuel classes or to estimation of the ligneaous component. We haphazardly selected eight areas, within the Site of Community Importance "Monteferrato e Monte Iavello" (Italy), where easy-to-measure characteristics (height, diameter, cover) of vascular plants were collected. Regression equations between easy-to-measure vegetation characteristics and biomass values were derived to estimate the biomass of each area in the two size classes. Then, we evaluated the relationships between the normalized difference vegetation index (NDVI) and the estimated biomass values for each area using regression equations and size class. The equations that resulted from the regression analysis were used to create maps of biomass using NDVI map. Such a procedure allows the identification of features otherwise lost when the vegetation is represented only by vegetation class labels. This includes the orientation of vegetation lines which may favor the spread of fire in a given direction; information that may be useful for hazard management and prevention.

Key words: Allometric equation, *Pinus pinaster*, *Erica scoparia*, biomass size class, Very High Resolution (VHR) satellite imagery.

INTRODUCTION

It is known that anthropogenic climate change and increasing human impact will lead to increased pressure on the environment, including natural and semi natural vegetation. Monitoring is considered essential and can be frequent and even cheap if satellite images are used. Indices relative to the biomass (such as greenness index and

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NDVI) are often used for evaluating biomass amount and vegetation health. This information is not enough and it is often necessary to have the distribution of biomass subdivided following some criteria. A common one, probably the most useful, is based on size classes which can help in estimating the amount of photosynthesizing biomass, or the amount of easy and quick to burn material, or the amount of ligneous material, which, once estimated at different time interval, can help the estimation of dead branches and trunk (this also important for fire hazard evaluation). In the case of biomass as fuel in wildfires biomass size, classes are important. Fires are predicted to potentially be more widespread and more frequent (Parry et al., 2007; Marlon et al., 2009) as the climate continues to be warm. Several studies indicate that the increase in the frequency of wildfires and the longer duration of the fire season are linked to increased spring and summer temperatures (Westerling et al., 2006), changes in the pattern of precipitation (Flannigan et al., 2000), and development of high fuel loads associated with long-term fire suppression (Schoennagel et al., 2004).

In the light of the scientific world's diagnosis of new climatic scenarios, wildfires in the Mediterranean basin represent a serious worry, considering that here wildfires are a common, and mostly human-induced feature where they have long played an important role in modifying vegetation patterns (Montenegro et al., 2004). Large-scale summer wildfires throughout the region have dramatically increased in the last few decades (Nunes et al., 2005; Bajocco and Ricotta, 2008; Catry et al., 2009; Ricotta et al., 2012), mainly as a consequence of rapid land-use changes (marginal rural land abandonment increasing fuel accumulation), socio-economic conflicts and competing interests, in conjunction with climatic warming which is reducing fuel humidity (Pausas and Vallejo, 1999).

In this context, spatial information on the distribution of fuel load (biomass weight) is a prerequisite for successful forest fire management and for predicting fire intensity and fire behaviour (Rothermel, 1972; Gray and Reinhardt, 2003). The fuel load determines the potential amount of heat that can be released during a fire, whereas the type and distribution of fuel elements affect their combustibility. Fine fuels burn more readily than coarse ones. Fine fuels react faster to weather changes, particularly if these fuels are dead, and they play a major role in the initial stages of all fires (Baeza et al., 2002). Fuel models considering the different types of biomass (fine and coarse) are an important factor that should be taken into consideration for fire planning, assessing fire risk, and improving fire prevention since fuel types may present completely different fire propagation rates and fire behavior.

The feasibility of modeling fuel/biomass distribution by remote sensing data has been frequently discussed in several studies and estimates of fire hazard and distribution maps of fuel have been provided (Vidal et al., 1994; Vidal and Devaux-Ros, 1995; Burgan et al., 1996; Riano et al., 2002; Rollins et al., 2004; Lasaponara and Lanorte, 2007). Nevertheless, the use of remote sensing images has been based on the analysis of medium- to high-resolution sensors, such as Landsat TM data without the subdivision of biomass into size classes.

Generally, satellite data are expressed in the form of spectral indices that attempt to enhance the spectral contribution of different features distributed over a surface. One of the most promising applications of satellite data is the estimation of biomass or primary productivity over time and space through satellite derived vegetation indices (Cihlar et al., 1991; Todd, 1998; Pettorelli et al., 2005). To be effective biomass estimators, spectral indices must be able to differentiate vegetation features; the characteristic reflectance pattern for green vegetation is low reflecting in the visible portion of the spectrum (particularly red) with a sharp increase in reflectance in the near-infrared portion. Vegetation indices respond to these expected differences in near-infrared and red reflectance. These broad-band vegetation indices have shown to be well correlated with canopy parameters related to chlorophyll and biomass abundance. For example, the normalized difference vegetation index (NDVI) is calculated as the difference between near-infrared and red reflectance values divided by the sum of near-infrared and red reflectance values. The Normalized Difference NDVI is a widely used surrogate of the amount (as green biomass) and vigor of vegetation at the surface (Tucker, 1979; Richardson et al., 1983; Christensen and Goudriaan, 1993). Previous studies have related NDVI values to different vegetation attributes such as plant biomass (Tucker et al., 1985; Persson et al., 1993; Hobbs, 1995), leaf area index (LAI) (Waring, 1983; Tucker et al., 1986; Gilabert et al., 1996), net primary production (NPP) (Tucker et al., 1981, 1983; Paruelo et al., 1997) and percentage of absorbed photosynthetically active radiations (APAR) (Asrar et al., 1984; Sellers et al., 1992).

In particular, the use of correlations between NDVI and biomass has been found to be unstable (Richardson et al., 1983; Tucker et al., 1983; Christensen and Goudriaan, 1993). This is because the reflection coefficients are primarily determined by green foliage biomass and not the amount of dry matter (Christensen and Goudriaan, 1993). Thus, in order to assess the efficacy of NDVI in estimating biomass size classes and their spatial distribution, field-based quantitative estimates of available living or dead vegetation weights are needed (Roussopoulos and Loomis, 1979; Mikaelian and Korzukhin, 1997; Sah et al., 2004).

An attractive means for estimating forest biomass is through the use of empirical allometric relationships (Whittaker and Woodwell, 1968; Usó et al., 1997). Allometry describes relations or mutual proportions between different plant organs or in general structural characteristics. Since measuring plant biomass in field conditions is laborious and extremely time consuming, empirical relationships or models are used to estimate the biomass from in-field, easily measurable, biometric variables such as

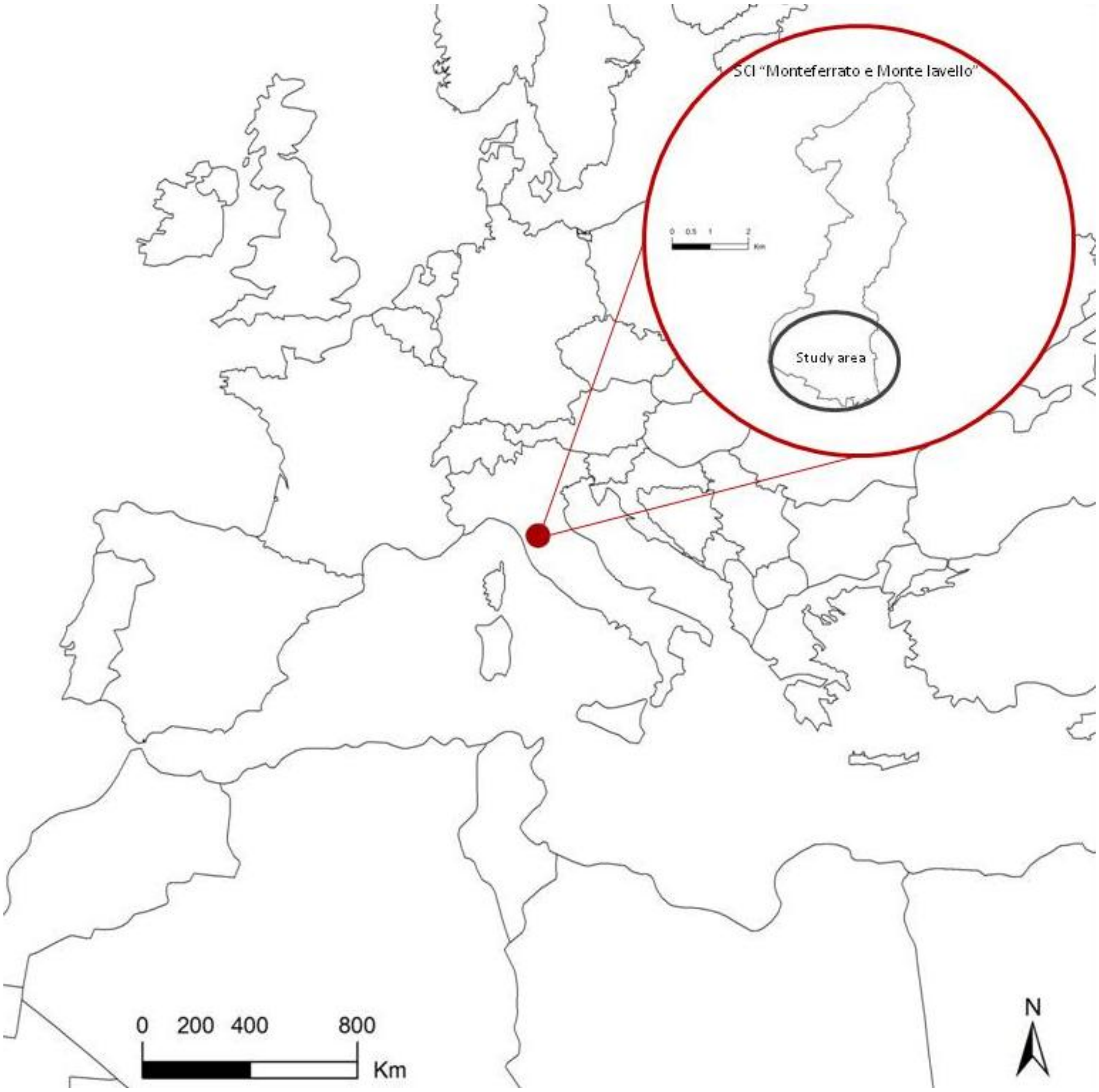

Figure 1. Location of the SCI "Monteferrato e Monte Iavello" (IT5140007) and the study area.

stem diameter, height, crown diameters or volume and crown cover. They have been used to estimate the biomass of trees, shrubs and herbaceous species in several environments (Assaeed, 1997; Ares and Fownes, 2000; Hierro et al., 2000; Zianis and Mencuccini, 2004; Northup et al., 2005; Pilli et al., 2006; Pokorný and Tomášková, 2007; Oñatibia et al., 2010).

The basic objective of this work was to develop a method for estimating biomass when subdivided into size classes and obtaining their distribution maps starting with the collection of simple vegetation characteristics and keeping the vegetation-destructive part of the sampling to a minimum. More specifically, this study aimed at: i) estimating biomass through the use of an allometric model based on relationships between biomass and vegetation characteristics directly measured in the field in some sample areas, ii) evaluating the potential of Very High Resolution (VHR) images (like QuickBird) for estimating biomass/fuel, iii) assessing the reliability of NDVI index to spatialise values of biomass and fuel throughout the study area.

MATERIALS AND METHODS

Study area

The study was carried out within the NATURA2000 site of community importance (SCI) "Monteferrato e Monte Iavello" (IT5140007; UTM32 667237E, 4867255N), located west of Florence, Tuscany (Figure 1). The SCI is approximately 1375 ha in area and ranges in elevation from 60 to 936 m a.s.l., with south slope exposure. Within this area, there are 530 ha of outcrops of ultramafic rocks with serpentine where we focused our observations. Here elevation ranges between 61 and 420 m a.s.l. Mean annual rainfall is approximately 1037 mm, October is the wettest month with 140 mm and July is the driest month with 31 mm. Mean annual temperature is 14.4°C. The average temperature of the coldest month (January) is 6°C and the average temperature of the warmest month (July) is 24.1°C (LaMMA and CSN, 2001). In the southern part of the SCI, there is

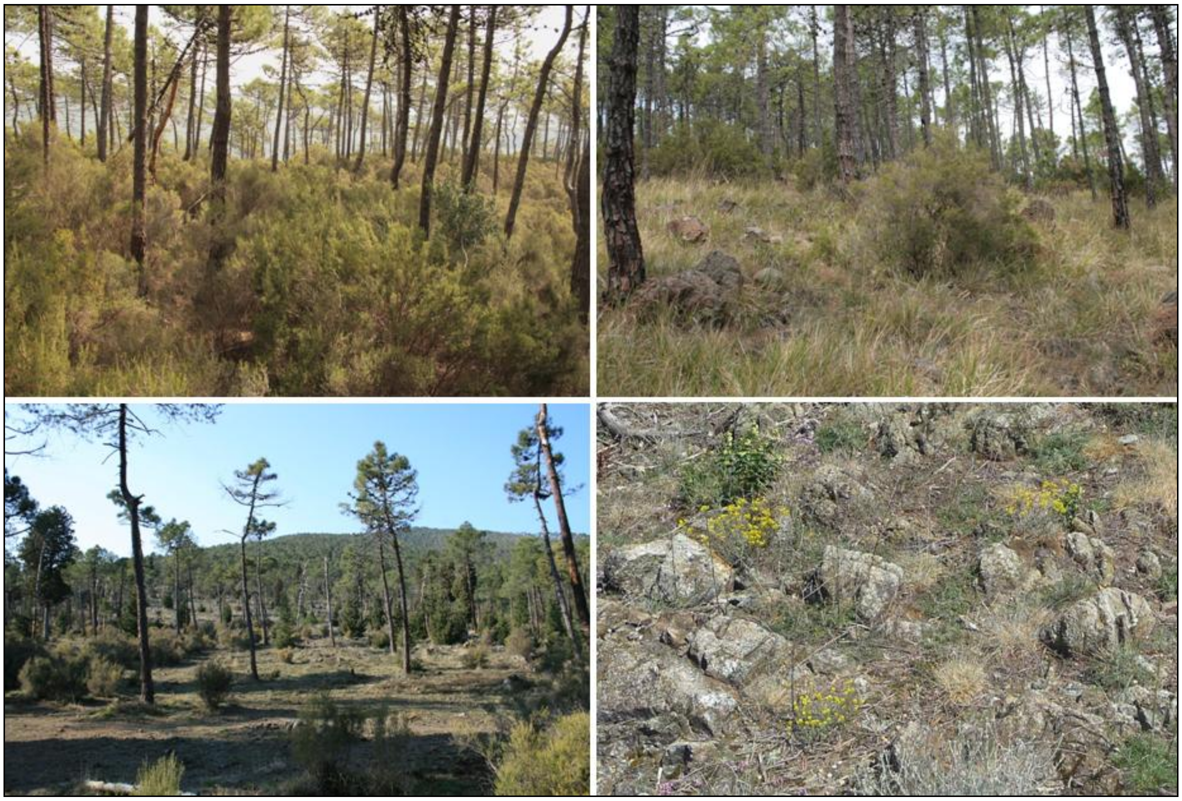

Figure 2. The four photographs illustrate different types of vegetation cover present in the study area.

the Centre of Natural Science (CSN), which hosts an important volunteer group of fire control and prevention.

The study area is characterized by evergreen mediterranean shrubland and woodland with dominance of the maritime pine (*Pinus pinaster*) (Figure 2), introduced from the 1st half of the 19th century; some individuals of cypress (*Cupressus sempervirens*), and oak (*Quercus ilex*). Heather (predominantly *Erica scoparia*) dominates the shrub layer, with laurel (*Laurus nobilis*), rock rose (*Cistus* spp) and myrtle (*Myrtus communis*). The herbaceous vegetation is characterized by perennial grasses and forbs such as *Brachypodium rupestre* and *B. pinnatum* which grow under the tree and shrub canopy, and *Helichrysum italicum*, *Alyssum bertolonii*, *Bromus erectus*, *Festuca* spp., which are found in more xeric situations. Furthermore, exposed stones are common in places and ferns, lichens and mosses are also typically present (Figure 2).

Field biomass sampling

Ground data were collected to extract the allometric relationships between dry weight and easily measurable plant parameters (EMPP: such as diameter, height, crown diameters, crown cover) in shrubs and herbaceous layers during the summer of 2011.

In the study area, a series of shrubs (*Erica scoparia*) were haphazardly selected to encompass a range of height, diameters, and crown forms, in order to obtain a sample of different size shrubs varying from smallest to largest. For each shrub, the following parameters were measured: i) two maximum crown diameters (taken at right angles to each other across the canopy of the shrub); ii) mean height obtained by measurements taken at many points, along transects running parallel or orthogonal to the major diameter (minimum number of observations was 10 values over 2 transects) (Figure 3). Afterwards, shrubs were cut at ground level and the fresh biomass was weighed with a portable scale.

A series of 60 x 60 cm plots were distributed with systematic sampling in the study area to collect herbaceous layer. For each sample, the percentage cover of herbaceous layer was estimated; all plant species were cut at ground level and weighed with a portable scale (1 g resolution).

In order to correctly evaluate the amount of biomass, the vegetation mass was arbitrarily divided into two size classes using the value of 1 cm as the delimiter between fine and coarse biomass. The size group <1cm of diameter (shrub leaves and fine parts of branches and sprouts, and herbaceous species) includes material that can ignite quickly and burn completely in a short time and the size group >1 cm (shrub coarse material) is mainly made of large small to large branches which will burn for a longer period but will ignite less quickly (Deeming et al., 1972). Chopped shrub and herbaceous species were placed in nylon bags, labeled, and transferred to the laboratory for calculating dry weight (oven-dried at 100°C until constant weight was reached). All components were then weighted separately, in order to calculate fuel load and fuel moisture for each class.

Then, for each sample of shrub and herbaceous species, we obtain: total biomass in g per each of the chosen dimension classes and their moisture content (water % of dry weight), the mean shrub height (m), two shrub diameters, area and volume of each shrub, percentage cover of herbaceous species.

For the tree layer, allometric equations were found to exist for similar pine forests (*Pinus pinaster*) during the literature review (Giovannini et al., 2001) and were used during this study, assuming that they were applied here too. Giovannini et al. (2001) related DBH and tree dry weight, dividing the dry weight in three fractions: total tree, fine wood (diameter <5 cm) and leaves.

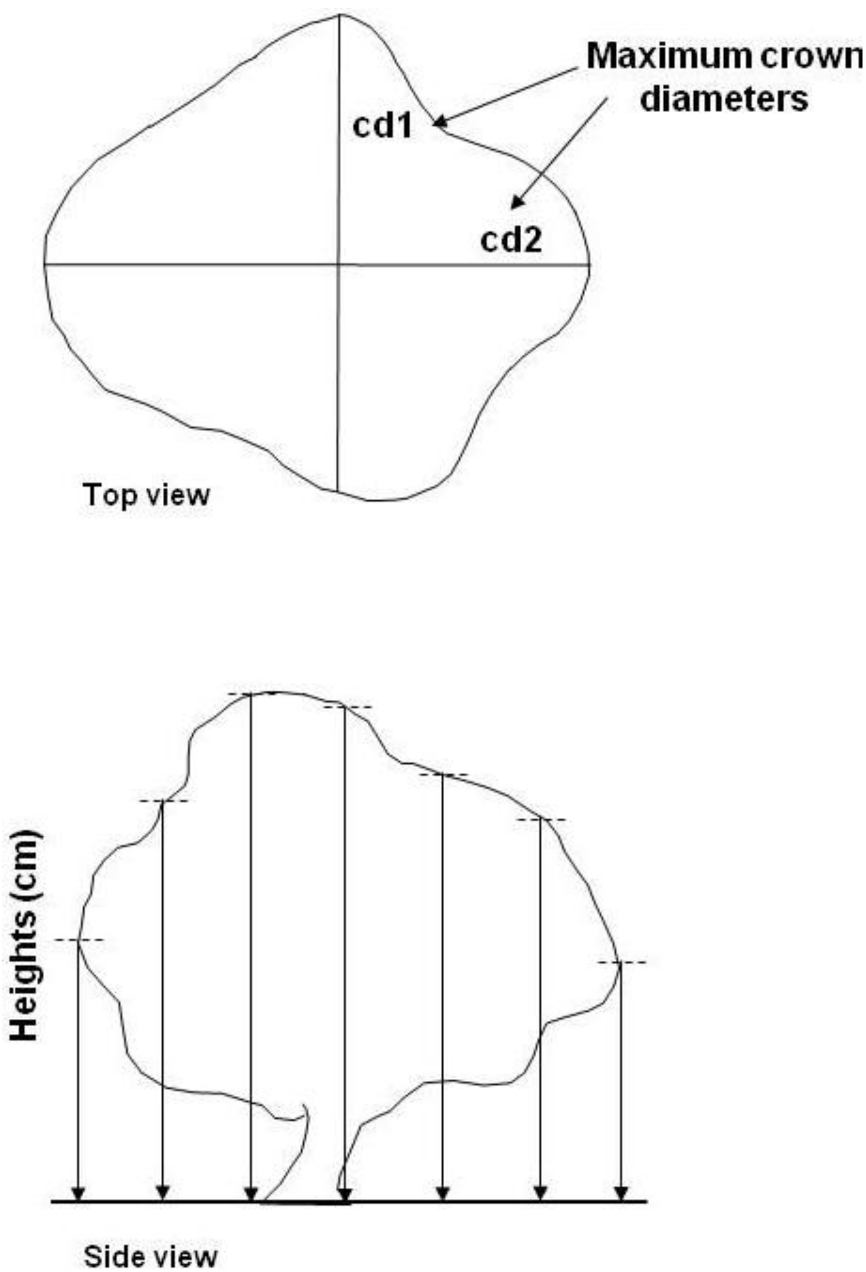

Figure 3. Top and side view of a typical shrub showing measurement technique used.

Spectral operations for estimating biomass patterns

A QuickBird multispectral image (spatial resolution 2.4 m; spectral resolution from 450 nm to 890 nm: four bands), acquired on 9 February 2009 (Figure 4), was pre-processed for both radiometric calibration and geometric corrections to ensure that each pixel in the image faithfully records the same type of measurement at the same geographic location over time (Kennedy et al., 2009) and to minimize the signal-to-noise ratio. Radiometric calibration included a linear transformation of the Image Digital Numbers (DNs) into Top of Atmosphere Radiance (TOARD) and then a non-linear transformation of TOARD into TOA Reflectance (TOARF) values ranging into [0,1], with these considered a parent class of surface reflectance values in an ideal (atmospheric-noise free) case (Baraldi et al., 2010). This assumption is made when ancillary data for atmospheric correction are not available. A geometric correction was performed in order to assign satellite images to their correct position on the Earth's surface (georeferencing) using Ground Control Points (GCP) as known points with a polynomial warping function and a nearest neighbor resampling to the Datum WGS84/UTM coordinate system.

From calibrated images, spectral indices can be extracted with the aim of enhancing the spectral contribution of vegetation while minimizing that of the background. The normalized difference vegetation index (NDVI) is one of the most widely used vegetation indexes and its contribution in satellite assessment and monitoring of global vegetation cover has been well demonstrated over the past two decades. It is defined as:

Figure 4. A true color image-map of the QuickBird scene acquired on 9 February 2009.

NDVI = (R_{NIR} – R_{RED})/(R_{NIR} + R_{RED})

Where, R_{RED}, and R_{NIR} represent surface reflectance averaged over visible (λ ~0.6 μm) and NIR (near infrared) (λ ~0.8 μm) regions of the spectrum, respectively. The NDVI is correlated with certain biophysical properties of the vegetation canopy, such as fractional vegetation cover, vegetation condition, and biomass.

Assessing biomass in georeferenced areas using NDVI

Once the allometric relationships between easy-to-measure plant parameters (EMPP) and biomass (dry weight) were established, we used them to estimate the biomass/fuel in georeferenced areas (polygons) with uniform vegetation types in terms of density. For each georeferenced area, we analysed the relationships between mean NDVI and estimated biomass values (fine and coarse) per unit area (t/ha) using linear regression models.

Within each stand, two areas were randomly selected. Understory vegetation (herbaceous and shrub layers) in each area was collected in square plots (1 x 1 m) 2 m spaced along belt transects. The number of plots was proportional to extent area. For all shrubs rooted in the plots, the following easy-to-measure plant parameters (EMPP) were determined: the longest crown diameter, the crown diameter perpendicular to the longest, total plant height the crown height of live foliage and the basal diameter (stem diameter just above ground level). Percent coverage of species in the herbaceous layer was recorded. Within each area, we measured the DBH (trunk diameter at breast height) and the height for each tree.

The regression models between EMPP and biomass values, allowed us to estimate the total biomass (fine and coarse) for shrub and herbaceous layers for each area through the application of the regression equations. For the tree layer, the total pine dry weight, the fine wood fraction and coarse fraction were estimated by DBH measurements using allometric models developed for similar pine forest in Mediterranean area by Giovannini et al. (2001). The biomass proportions were summed to give the tree biomass.

Statistical approaches for estimating biomass

Regression analyses were performed to determine the relationship between biomass and EMPP. The independent variables used were crown diameters (cd1, cd2), mean height (H), crown area (ca) of shrub plants and percentage cover of herbaceous plants. The dependent variables were fine, coarse and total biomass and were tested for normality of distribution using the Shapiro-Wilk test (Shapiro and Wilk, 1965), and if necessary transformation was made.

Linear (Y = βo+ β1*X1) or non linear regression models (Y = dry weight of biomass in grams, X1…Xn are the respective explanatory variables in each model) were used to assess the choice of independent variables and predictive equations selected based on adjusted R^2 values and the significance (p-value) of the regression coefficients. GIS analyses were performed with GRASS (GRASS Development Team, 2011) and statistical analyses using R 2.13.1 for Windows (R Development Core Team, 2011).

RESULTS

The allometric models based on regression equations models all resulted as statistically significant and explained between 66 (R^2 = 0.66) and 93% (R^2 = 0.93) of the variability in individual biomass (fine and coarse). In parti-

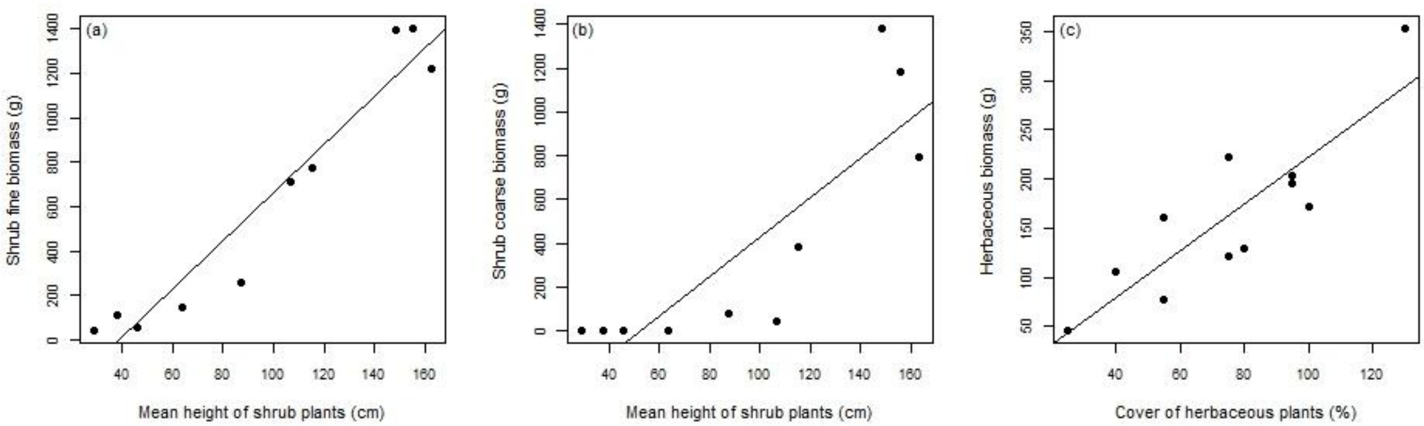

Figure 5. Scatter plots between shrub fine, shrub coarse and mean high of shrub and between herbaceous biomass and percentage of herbaceous plants cover.

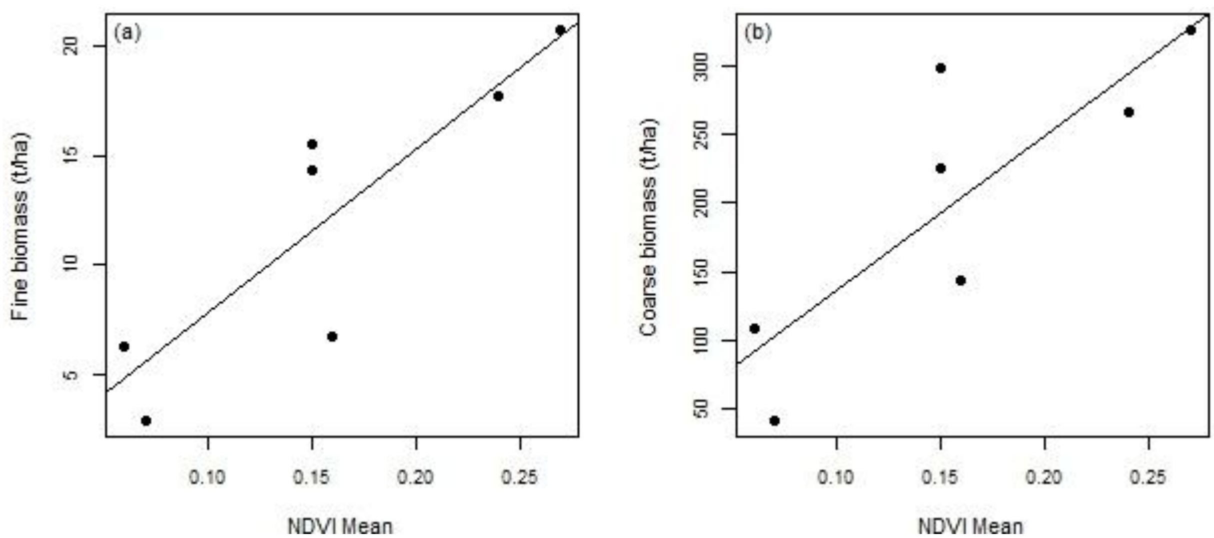

Figure 6. Scatter plot between NDVI and fine and coarse biomass.

cular, results of the regression analysis indicate that the mean height was the variable that best predicted fine and coarse shrub biomass (Table 1). The linear relationships with R^2 above 0.7 were chosen as the best fitting equations to the predicted fine and coarse fuel biomass (Table 1). Figure 5 shows the scatter plot of best relationships obtained by regression analyses: mean height of shrub plants plotted against fine and coarse shrub biomass displayed a positive trend as scatter is significant. Likewise, the scatter plot between percent cover of herbaceous plants and herbaceous biomass indicated a good relationship. These scatter plots can give an idea of the effecttiveness of EMPP in investigating its relationship with biomass.

Allometric analysis showed that the percentage of coverage of herbaceous species is an effective allometric measure for predicting the biomass in the herbaceous vegetation layer, since the regression result was statistically significant (Table 1). The NDVI index, performed on QuickBird images with Very High Resolution, confirmed itself as a good predictor of fine and coarse dry weights for estimating biomass/fuel in this area, as reported in Table 2. Figure 6 shows mean NDVI plotted against fine and coarse biomass.

The coefficients results obtained from the regression analysis were used to distribute the fuel values on the area of interest and to create a fine-fuel map and coarse-fuel map (Figure 7a, b). The fine fuel ranged from 0.02 to 20 t/ha and the coarse fuel ranged from 0 to 320 t/ha.

DISCUSSION

The knowledge of how the distribution of natural biomass weights subdivide into size classes is important for improving current fire prevention and fire behavior modeling,

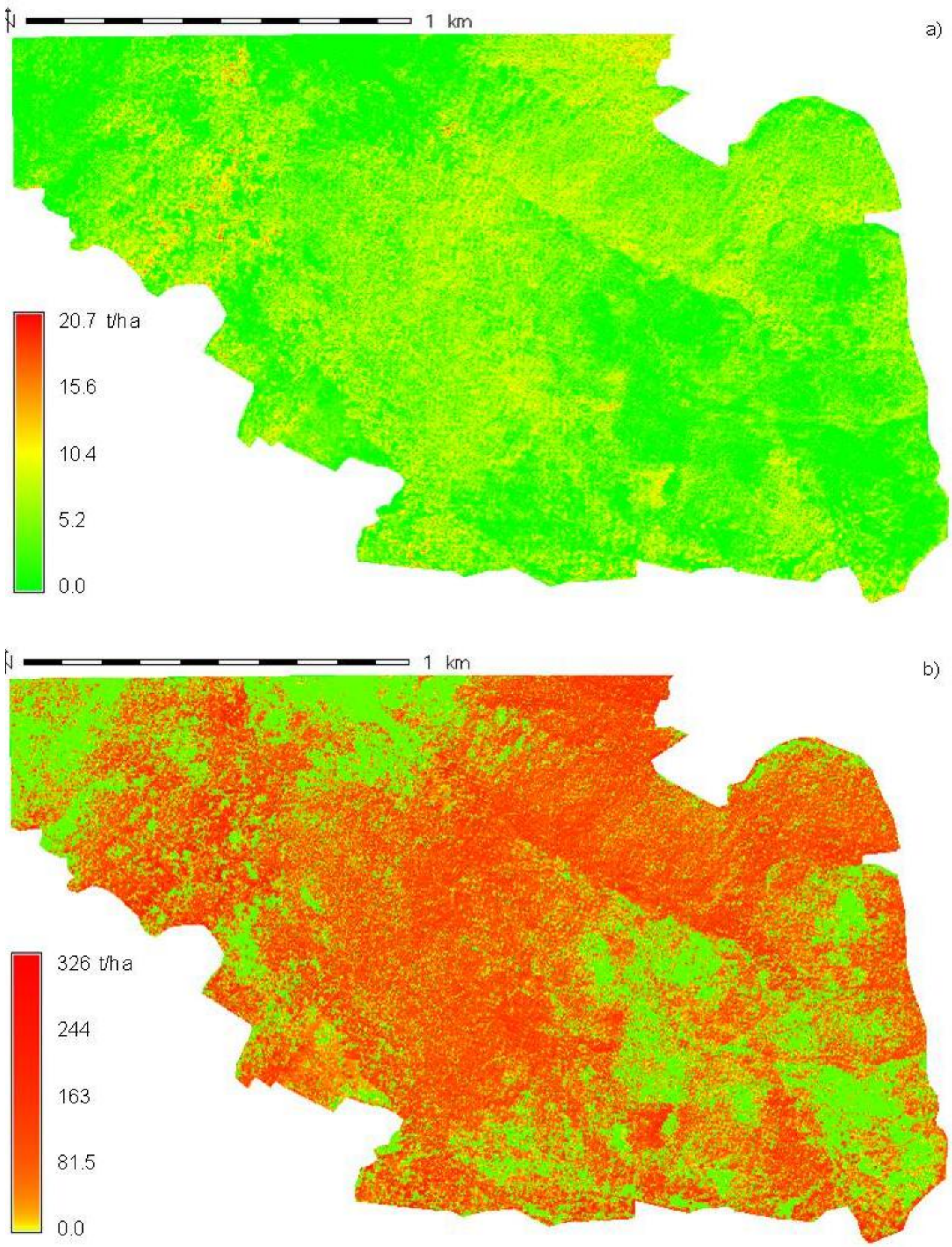

Figure 7. Distribution of fine (A) and coarse (B) biomass (t/ha) in the study area.

which can alleviate the negative impacts of fire on the ecosystem. It may also be important in order to follow the production of vegetation dead mass and other issue where leaves need to be separated by more ligneous components. Information on the spatial distribution of biomass weights in terms of fine and coarse types is essential for understanding where fuel is denser or where it is discontinuous and the different fire propagation rates and fire behavior. For example, a considerable part of the study area was depleted of vegetation, hence, following

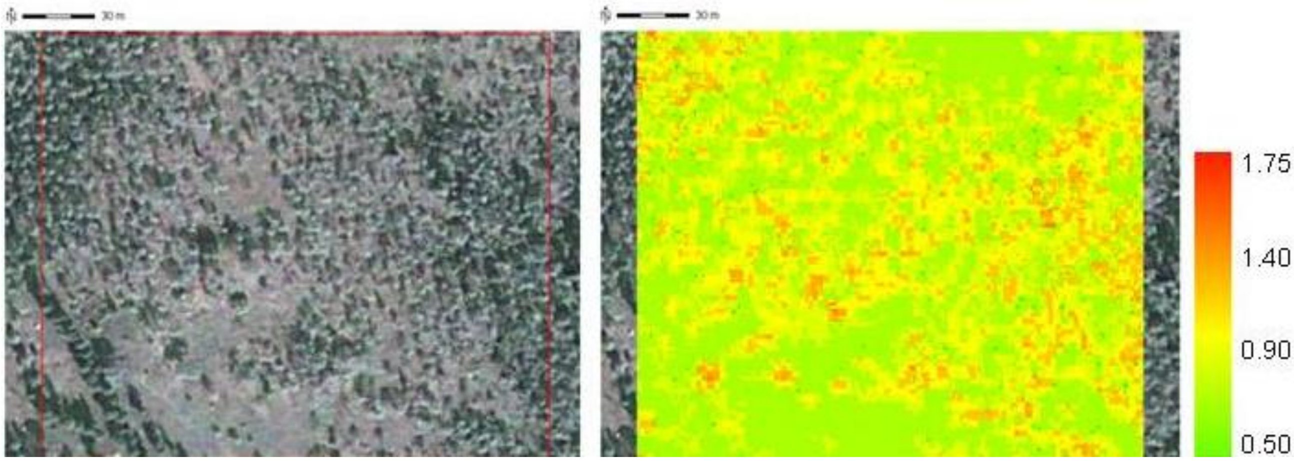

Figure 8. Detail of fine fuel map.

CORINE land cover classification or even a classification based on two-stage hierarchical system (Baraldi et al., 2010; Blonda et al., 2011), it was classified as bare soil where no fuel would have been allocated. With this type of fuel distribution, it is clear that this underestimates the fine particles, the part of the vegetation that contributes most in the propagation of the forest fire. Furthermore, the model developed in this paper, allows the identification of features otherwise lost when the vegetation is represented only by vegetation class labels. This includes orientation of vegetation lines which may favor the spread of fire in a given direction, information that may be useful for hazard management and prevention (Figure 8).

Estimates of biomass and fuel loadings are necessary for many applications in the fields of fire management, ecology, biomass, and bioenergy research. However, the use of destructive sampling to provide these estimates is time consuming and expensive, and furthermore, in protected sites, there are strong restrictions on cutting vegetation, making difficult the acquisition of fuel distribution. In this paper, statistical regression models were used to derive allometric equations for biomass by fuel size categories. Numerous studies have assessed the relationship between vegetation structure and fuel biomass and among which some authors have reported that total bio-mass in shrubland ecosystem was closely related to height and vegetation cover (Ohmann et al., 1976; Buech and Rugg, 1995; Fogarty and Pearce, 2000; Sağlam, 2008). The correlations of vegetation height provided in our study also coincide with that described by Fernandes (1998) in Portuguese shrubland and by Rittenhouse and Sneva (1977) of Wyoming big sagebrush.

Available fuel biomasses are very important for the spreading and intensity of fire. In this study, average fine biomass was 3.8 t/ha, while average coarse biomass was 47.5 t/ha and average total biomass was 38 t/ha. Similar results were found in some Mediterranean shrublands (Specht, 1969; Icona, 1993; Dimitrakopoulos, 2002; Sağlam, 2008).

A close relationship was found in this study between NDVI and biomass, and consequently the vegetation index gave an indicator of fuel biomass. Numerous studies are now using NDVI as a proxy of vegetation productivity instead of performing direct vegetation assessments (Kerr and Ostrovsky, 2003; Pettorelli et al., 2007; Wittemyer et al., 2007). Studies have revealed some discrepancies regarding the shape of these relationships (quadratic, log-linear, linear relationships between NDVI and vegetation biomass (Hobbs, 1995; Gilabert et al., 1996; Schino et al., 2003), respectively). However, due to the variety of statistical approaches used, it remains unclear whether these discrepancies reveal true biological differences, such as differences in plant community characteristics, or methodological concerns.

In this study, the relationships found between NDVI and biomass was used to distribute the biomass values on the area for creating maps of fine and coarse biomass components. Maps, in particular, are essential for computing fire hazard spatially and for assessing fire risk by their use in models simulating fire growth and intensity across a landscape (Keane et al., 2001). Biomass distribution maps account for structural characteristics of vegetation related to fire behavior and fire propagation. Remote-sensing data is becoming the primary method in fuel classification and mapping efforts. Satellite sensors provide digital information that can easily be tied into other spatial databases using GIS analysis, which can be imported into fire behavior and growth models.

Knowing the amount of biomass and other fuel characteristics across a landscape is becoming increasingly important to fire managers as a new generation of fuel and fire management decision support systems come on line. With accurate fuel information, fire managers should be able to make better-informed decisions about ongoing wildland fires and fuel treatments.

The originality of our study resides in the presentation of a new modeling approach that uses NDVI and field vegetation data to create distribution maps of biomass. It

Table 1. Regression models for estimation of shrub biomass by Cd1 (first max diameter of crown shrub), Ca (Area shrubs), Ch (mean height of shrub), Hcover (herbaceous cover).

Dependent Variables	Predictor variables	Constant and coefficients	F	R^2Adj
Shrub coarse biomass	Cd1	a: 3.49 b: -11.37	18.71	0.639**
	Ca	a: 1.72 b: -10.83	20.53	0.661**
	Ch	a: 0.01 b: -0.512	17.19	**0.789****
Shrub fine biomass	Cd1	a: 1.59 b: -0.94	50.11	0.830***
	Ca	a: 0.72 b: -0.18	25.83	0.713***
	Ch	a: 2.22 b: -4.06	150	**0.937*****
Herbaceous biomassb	Hcover	a: 0.09 b: -1.07	21.29	**0.833****

Significance code: ***,P<0.001; **, P<0.01.

Table 2. Regression models for estimation of biomass by NDVI.

Dependent variables	Predictor variables	Constant and coefficients	F	R^2 Adj
Fine biomass	NDVI Mean	a: 3.36 b: -0.24	17.4	0.701**
Coarse biomass	NDVI Mean	a: 51.07 b:-4.04	9.01	0.612*

Significance code: **, P<0.01; *, P<0.05)

demonstrates that it is possible to spatially distribute several biomass characteristics by: 1) locally determining allometric relationships, 2) using them in a series of geo-referenced polygons for evaluating local values of the chosen biomass characteristics, 3) determining relationships between radiometric indices and the chosen biomass characteristics using biomass and radiometric characteristics calculated in each polygon, and finally 4) using the radiometric indices to spread the biomass characteristics values in the landscape.

Particularly, in this study, the relationships found between NDVI and biomass were used to distribute the biomass values on the area for creating maps of fine and coarse biomass components. Our model does not require the use of ancillary variables (Riaño et al., 2002) and is based on relationships between fine and coarse biomass and NDVI. Other authors used supervised classification techniques on low resolution imagery (such as Landsat TM) to generate the fuel maps and did not take into account fine and coarse fuel (Vidal et al., 1994; Vidal and Devaux-Ros, 1995; Burgan et al., 1996; Riano et al., 2002; Rollins et al., 2004; Lasaponara and Lanorte, 2007).

In conclusion, in this study carried out in *Pinus pinaster* dominated sites, we developed a series of regression equations for predicting fine and coarse fuel biomass of species common in a Mediterranean region, mainly *Erica scoparia*. The regression models developed herein are suitable for predicting fuel biomass in similar shrub areas. Local and site-specific fuel biomass data should be used for more reliable fire behavior predictions. Given the range of the data on which the relationships were based, this study provides a valuable contribution to biomass research in general. However, it should be kept in mind that the range of fuel characteristics on which the relationships were based represents the range of conditions under which it is possible to use the relationships generated through this study.

ACKNOWLEDGMENTS

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